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# Habits as adaptations: An experimental study <sup>☆</sup>

Ludmila Matysková <sup>a</sup>, Brian Rogers <sup>b</sup>, Jakub Steiner <sup>c,d,\*</sup>, Keh-Kuan Sun <sup>b</sup>

<sup>a</sup> University of Bonn, Germany

<sup>b</sup> Washington University in St. Louis, United States of America

<sup>c</sup> University of Zurich, Switzerland

<sup>d</sup> CERGE-EI, Czech Republic



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## ABSTRACT

When observable cues correlate with optimal choices, habit-driven behavior can alleviate cognition costs. We experimentally study the degree of sophistication in habit formation and cue selection. To this end, we compare lab treatments that differ in the information provided to subjects, holding fixed the serial correlation of optimal actions. We find that a particular cue – own past action – affects behavior only in treatments in which this habit is useful. The result suggests that caution is warranted when modeling habits via a fixed non-separable utility. Despite this sophistication, lab behavior also reveals myopia in information acquisition.

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## 1. Introduction

Habits play an important role in economic discourse. Economists employ them to explain diverse phenomena ranging from inertia of consumption to brand loyalty. Often, the standard modeling approach accounts for habits via the use of a fixed time-nonseparable utility function, thus leaving the issues of when and why habits form, and their responses to counterfactual environments, unaddressed. On the other hand, psychologists offer a view on both the purpose of and the mechanism underlying habit formation. In this literature, habits are typically defined as automated responses triggered by cues, where cues are past actions or other variables that empirically correlate with optimal continuation choices. In this view, the purpose of habits is to alleviate cognition costs; see Andrews (1903), Lally et al. (2010), and Wood and Neal (2007).

We explore the extent to which people's behavior exhibits sophistication in habit formation and cue selection in a simple setting. This issue is crucial for an assessment of the common modeling approach to habits within economics. To the extent such sophistication is observed, it suggests that habits, at least in some economic applications, should be understood as endogenous, changing in predictable ways with the decision-making environment. Our main experimental results largely

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\* Corresponding author.

E-mail addresses: [ludmila.matyskova@cerge-ei.cz](mailto:ludmila.matyskova@cerge-ei.cz) (L. Matysková), [brogers@wustl.edu](mailto:brogers@wustl.edu) (B. Rogers), [jakub.steiner@cerge-ei.cz](mailto:jakub.steiner@cerge-ei.cz) (J. Steiner), [sun.k@wustl.edu](mailto:sun.k@wustl.edu) (K.-K. Sun).

support this position. Our subjects do form a habit when available cues are predictive of the current optimal choice and they do not form a habit otherwise, i.e., when the available cues cease to be informative guides for current choices. When multiple informative cues are available, subjects select the most informative one. We view these findings as suggesting that habit formation is a predictable response to changes in the decision-making environment. An understanding of habit formation rooted in optimization can inform analysts which cues, out of several available cues, a decision-maker is likely to leverage. Modeling habits as optimal adaptations also permits counterfactual predictions of habit strength under various policies.

To study sophistication in habit formation, we compare treatments from a lab experiment in which subjects face a sequence of tasks generated by a given stochastic process. The compared treatments differ only in the information feedback. If habits consist of naive repetitions of past actions, then the variation in feedback should not impact habit formation. Our data, however, show that subjects form habits with distinct cues across these treatments; moreover, the cues selected are naturally rationalized as adaptations to the information provided.

In our experiment, the basic task confronted by subjects is to recognize a binary state variable presented visually on a computer screen. Correctly identifying the state requires moderate cognitive effort.<sup>1</sup> Each decision problem consists of a two-period sequence of this state-recognition task, across which the state evolves according to a known stochastic process with positive serial correlation. In the treatment without feedback, we reveal both realized states to the subjects only at the conclusion of the two-period sequence. We find that subjects form a habit in this treatment: the first-period outcome predicts the second-period choice (controlling for the second-period state) in this treatment. The cue that subjects leverage is their first-period *action*; the first-period state does not predict the second-period action. In other words, the behavioral pattern exhibits action inertia. The habit alleviates the subject's cognitive burden since, due to the serial correlation of the states, the first-period action contains useful information about the second-period optimal choice, and the subjects utilize this information.

In the other treatment, with information feedback, we employ an identical state-generating process, but we reveal the first-period state before the second period task, so that subjects now know the first-period state before engaging in the second task. Subjects again form a habit in this treatment: payoff-irrelevant elements of the history predict the continuation choice (controlling for the second-period state). However, importantly, the cue changes relative to the previous treatment. The first-period action is no longer predictive; all of the predictive power is associated with the first-period state, which contains superior information about the optimal continuation action relative to the first-period action. This result suggests that our subjects demonstrate sophistication in the sense that they select cues according to their informational content. As a further check, we ran additional treatments (both with and without information feedback) in which the states were serially independent, so that the first period history contains no cues that correlate with the optimal second-period choice. As expected, subjects do not form habits in these treatments; the second-period choice is independent of all first-period variables (for both information treatments).

To the extent that habits are driven by optimal adaptations, their strength should vary predictably with the parameters of the environment, in particular, with the incentive stakes and the serial correlation of states. When stakes are decreased or correlation increased, the trade-off between reliance on the cues and the acquisition of new information shifts in favor of the cues. Thus, we predict that habits become stronger – cues become more predictive of continuation behavior – when stakes are lower and correlation is greater. We test this hypothesis experimentally. For the correlated treatments, changes in stakes and correlation have no impact on the cue selection, but they do affect the strength of habits. We obtain strong statistical evidence in favor of the predicted comparative statics when the selected cue is the past action. When the cue is the past state, the evidence continues to support the prediction, although it is less conclusive.

While, as discussed, some sophistication is observed in how subjects select and use cues in making their second-period choices, we also find indirect evidence of myopia in the information-acquisition process. When states are correlated and feedback is not provided then information is more valuable in the first period relative to the second period, since first-period information is useful in both periods. Consequently, a forward-looking decision-maker should acquire more information in the first than in the second period, and this should be manifested in the observed accuracy of choices. Since we do not observe differences in the accuracy of choice across periods, we conjecture that the subjects do not fully internalize the continuation value of information.

We analyze the experimental data through the predictions of a model that derives habit formation from primitive assumptions on the information-processing friction. In the model, a decision-maker chooses information structures (i.e., a strategy for how to acquire information about the state), trading off the precision of her information against an acquisition cost. The model allows us to formalize the above intuitive predictions about habit formation, cue selection, and the comparative statics of habit strength, as testable hypotheses that derive from the model's implications regarding optimal behavior.

Having summarized our findings, let us comment on their interpretation. As mentioned, part of the significance of our results derives from comparisons with how habits are understood and modeled in various contexts. Popular macroeconomic models explain the empirically observed inertia of consumption by imposing a time-nonseparable utility function

<sup>1</sup> Identifying the state amounts to conducting a counting process, so that we can plausibly assume that frictions in the cognitive process are the main source of errors.

$u(c_t - c^{t-1})$ , where  $c^{t-1}$  is an aggregate of the consumption history, e.g. Pollak (1970) and Abel (1990). When  $u$  is concave, high past consumption triggers high current consumption; i.e.,  $c^{t-1}$  becomes the cue underlying a consumption habit. Since the assumed utility representation is exogenous, the modeling choice of the aggregate  $c^{t-1}$  is not obvious and specifications in the literature include aggregates of past population-wide consumption, past individual consumption, and past individual consumption of specific categories of goods; see Schmitt-Grohé and Uribe (2007) for a review. If, as suggested by our data, habit formation and cue selection is endogenous, responding to changes in the environment, then optimization-based models may offer insight into which habits form in which contexts and their associated comparative statics. Yet in other contexts, such as in the case of physiological dependencies akin to smoking, time-nonseparable utility functions may capture the causes of action inertia well. Relatedly, our experiment has indicated sophistication in habit formation in a specific environment which involves, in particular, a small number of task repetitions. Whether such sophistication extends to a larger number of repetitions of a basic task (along with a possibly more complex state process), in which largely automated behavior is perhaps more likely to be triggered, is an open question.

Other fields offer an alternative view, beyond the preference-based formulation mentioned above, on the ways in which habits are developed. Psychologists and neuroscientists emphasize procedural aspects of habitual behavior: it is automatic, largely subconscious and fast, in contrast to a deliberative decision-making process. Another defining aspect of habits within neuroscience is behavior-based: habits are triggered by historically formed cues and they may continue to be employed beyond the span of their functionality (e.g. Dezfouli and Balleine (2012)). Our definition of habits falls within this last, behavior-based approach; we say that a habit is formed if the first-period variables, irrelevant for the second-period payoffs, nonetheless predict the second-period behavior.

Within this literature, the closest papers to our work are Laibson (2001) and Camerer et al. (forthcoming). Laibson (2001) proposes a model of habit formation rooted in psychological forces that, like ours, focuses on an endogenous selection among several available habit cues, albeit, unlike in our case, the cue selection is not rooted in the optimization of cognition costs. Camerer et al. (forthcoming) study a model of habit formation inspired by neuroeconomics. They specify an automatic process which governs switches between a habitual (model-free) mode and a preference-based mode of optimization (model-based). The habitual mode is dictated by a simple automatic procedure, in which historically successful actions are reinforced in a reward-contingent loop.

Most directly, our model of habit formation belongs to the rational-inattention literature originating in Sims (2003). It builds, in particular, on the discrete dynamic rational-inattention model by Steiner et al. (2017), which in turn extends a static model by Matějka and McKay (2015). Rational inattention models have been used to derive inertia of behavior in a macroeconomic context, see Mackowiak and Wiederholt (2009) for a theoretical contribution and Khaw et al. (2017) for an experimental exploration. Khaw and Zorrilla (2018) find that lab subjects develop action inertia in a saving problem and, like us, the authors interpret the observed inertia as habits.<sup>2</sup>

## 2. Model and hypotheses

We study habit formation in the simplest possible setting. A decision-maker (DM) chooses a binary action  $a_t \in \{0, 1\}$  in each of two periods and receives  $\sum_{t=1}^2 u(a_t, \theta_t)$ . The binary state  $\theta_t \in \{0, 1\}$  evolves according to a stochastic process known to the DM. The first-period state attains value 1 with prior probability  $p_1$ , and  $\theta_2 = \theta_1$  with probability  $\gamma \geq \frac{1}{2}$  for each value of  $\theta_1$ . The two states are independent when  $\gamma = \frac{1}{2}$ , and they are positively correlated when  $\gamma > \frac{1}{2}$ . In the latter case, we say that the states are persistent. The DM's task in each period is to match the action to the state;  $u(a, \theta) = s$  if  $a = \theta$  and zero otherwise;  $s > 0$  is the stake.

We allow for (and focus on) the possibility that even though the state realizations are available for the DM's inspection, establishing complete information is costly. Consequently, behavior is stochastic.

### 2.1. Definitions

We now introduce terminology to allow us to define habits in the context of dynamic stochastic choice.

An analyst collects data on the states and actions across many repetitions of the two-period decision problem. In its idealized form, the analyst observes the joint probability distribution  $p(\theta_1, a_1, \theta_2, a_2)$  over the quadruples of states and chosen actions. Our data extend the state-dependent stochastic-choice data introduced by Caplin and Dean (2015) in a static setting to the dynamic context considered here.

We say that the DM *forms a habit* if there exists a triple  $(\theta_1, \theta_2, a_1) \in \{0, 1\}^3$  such that  $p(a_2 | \theta_2, \theta_1, a_1) \neq p(a_2 | \theta_2)$ . Otherwise, if  $a_2$  is independent of  $(\theta_1, a_1)$  conditional on  $\theta_2$ , we say that the DM *does not form a habit*. Thus, the DM forms a habit if the history of the process – which is irrelevant to the continuation payoff – predicts continuation behavior. Our definition of habits is behavioral in nature and distinct from the commonly used non-separable utility approach. Our analyst knows that the DM's utility is, in fact, time-separable; she attributes any correlation between the history and continuation behavior to imperfections in the decision-making process, and refers to the predictive power of the history as a habit.

<sup>2</sup> Within information-based approach to habits, Angeletos and Huo (2018) prove the observational equivalence between a model featuring higher-order uncertainty, and a model of a representative agent with consumption habits.

Additionally, we define cues that drive the habitual behavior. Is the habitual behavior in the second period, if it arises, triggered by the past state  $\theta_1$ , or by the past action  $a_1$ ? Let  $z$  be one of the two random variables in the set  $\{\theta_1, a_1\}$  and  $w$  be the complementary variable from this set. We say that  $z$  is the cue for the habit if (i)  $p(a_2 = 1 \mid \theta_2, z = 1) > p(a_2 = 1 \mid \theta_2, z = 0)$ , and if (ii)  $p(a_2 = 1 \mid \theta_2, z, w) = p(a_2 = 1 \mid \theta_2, z)$ . Thus, for instance, the past action  $a_1$  is the cue for the habit if the probability that the DM chooses the high action in the second period increases with  $a_1$  given  $\theta_2$ , and  $\theta_1$  has no additional predictive power. The latter condition prevents a spurious identification of cues. Since  $\theta_1$  and  $a_1$  may be correlated (and indeed are correlated in our data), it may happen that they both correlate with continuation behavior, but all the predictive information is contained in only one of them.<sup>3</sup>

The correlation between cues and continuation behavior may vary with the DM's environment; hence, habits may exhibit a continuous range of strength. We capture this as follows. Suppose that the DM has developed a habit with cue  $z \in \{\theta_1, a_1\}$ . For a state value  $\theta \in \{0, 1\}$ , we define the *habit strength*  $\phi_z(\theta)$  at state realization  $\theta_2 = \theta$  to be

$$\phi_z(\theta) = \frac{p(a_2 = \theta \mid \theta_2 = \theta, z = \theta)}{p(a_2 = \theta \mid \theta_2 = \theta, z = 1 - \theta)},$$

which measures how strongly the probability that the DM chooses the correct  $a_2$  varies with the cue value in the state  $\theta_2 = \theta$ .

## 2.2. A rational-inattention model of habit formation

We model habits as optimal adaptations to an information-processing friction. This is operationalized by allowing the DM to choose among information acquisition procedures that differ both in their overall precision and also in the distributions of various types of errors. That is, the DM conducts costly statistical experiments that produce signals  $x_t$  in periods  $t = 1, 2$ . Additionally, in between periods 1 and 2, she receives an exogenous signal  $y$  that captures possible experimental feedback between periods. In each period  $t$ , the DM chooses an action according to a pure action strategy  $\sigma_t$  that maps the observed signals up to period  $t$  to  $a_t$ :  $a_1 = \sigma_1(x_1)$  and  $a_2 = \sigma_2(x_1, x_2, y)$ . The DM controls the experiments that generate  $x_t$  and can condition the employed experiment on all the available information at the given period: Let  $X$ ,  $|X| \geq 2$ , be a fixed signal space. The DM can choose any first-period experiment  $f_1(x_1 \mid \theta_1)$  and any system of second-period experiments  $f_2(x_2 \mid \theta_2, x_1, y)$  that govern the conditional probability distribution of the signals  $x_t \in X$  for each combination of the values of the random variables specified in the condition. The signal  $x_1$  is constrained to be independent from  $\theta_2$  conditional on  $\theta_1$ . Similarly,  $x_2$  is constrained to be independent from  $\theta_1$  conditional on  $(\theta_2, x_1, y)$ ; the DM learns about  $\theta_t$  only in period  $t$ .

We consider two distinct processes that generate the exogenous signal  $y$ . In one case,  $y$  perfectly reveals the first state;  $y = \theta_1$ , and we say that the *DM receives feedback*. In the other case,  $y = y_0$ , where  $y_0$  is an arbitrary constant, and we say that the *DM does not receive feedback*.

Following the rational-inattention literature, we specify a uniformly posterior-separable information cost; see Caplin et al. (2017). Let  $H : [0, 1] \rightarrow \mathbb{R}$  be a strictly concave function. The cost of the first-period experiment  $f_1(x_1 \mid \theta_1)$  is

$$I(\theta_1; x_1) = E_{\hat{q}_1} [H(p_1) - H(\hat{q}_1)]$$

where  $p_1$  is the prior probability that  $\theta_1 = 1$  and  $\hat{q}_1 = \Pr(\theta_1 = 1 \mid x_1)$ . Together with the literature, we interpret  $H(q)$  as the measure of uncertainty associated with the belief that assigns probability  $q$  to  $\theta_1 = 1$  and  $I(\theta_1; x_1)$  is the expected reduction of this uncertainty achieved by the observation of the signal  $x_1$ . When  $H$  is Shannon entropy, then  $I(\theta_1; x_1)$  is the mutual information between the random variables  $\theta_1$  and  $x_1$ , and the information cost coincides with that in Sims (2003). Analogously, for any given signal realizations  $x_1$  and  $y$ , the cost of the second-period experiment is

$$I(\theta_2; x_2 \mid x_1, y) = E_{\hat{q}_2} [H(p_2) - H(\hat{q}_2) \mid x_1, y],$$

where  $p_2 = \Pr(\theta_2 = 1 \mid x_1, y)$  is the DM's belief about  $\theta_2$  at the beginning of the second period and  $\hat{q}_2 = \Pr(\theta_2 = 1 \mid x_1, y, x_2)$  is the posterior belief. The DM maximizes her expected net payoff.<sup>4</sup> She solves

$$\max_{f_1, f_2, \sigma_1, \sigma_2} E[u(\sigma_1(x_1), \theta_1) + u(\sigma_2(x_1, x_2, y), \theta_2) - I(\theta_1; x_1) - I(\theta_2; x_2 \mid x_1, y)].$$

Let  $p(\theta_1, a_1, \theta_2, a_2)$  be the joint distribution of the states and actions generated by the optimal experiments  $f_1^*$  and  $f_2^*$  and action strategies  $\sigma_1^*$ ,  $\sigma_2^*$ . We impose a regularity condition that all quadruples  $(\theta_1, a_1, \theta_2, a_2)$  are attained with positive probabilities. The condition holds when the cost function is sufficiently scaled down, and is satisfied in our experimental data.

<sup>3</sup> Our definition of cues has roots in cognitive psychology and neuroscience. These fields conceptualize habits as tendencies to choose actions that have been previously rewarding (e.g. Dezfouli and Balleine 2012). Since our first-period cues correlate with the optimal first-period actions, conditioning on the cues correlates the second-period choices with the first-period optimal choices.

<sup>4</sup> We abstract from the optimization process. It is likely that lab subjects cannot directly solve for the optimal information acquisition procedure, nor do they know costs of all information acquisition procedures. A promising direction for a study of the optimization process is that of reinforcement learning; e.g. Roth and Erev (1995) and Watkins and Dayan (1992).

**Lemma 1.** *The optimal joint distribution  $p$  of states and actions is unique.*

Proofs are in the Appendix.

The next proposition characterizes the patterns of habit formation that arise under optimal information acquisition. In particular, the model predicts that habits are formed only if the available cues contain useful information about optimal continuation choices and that, in such cases, the most informative available cue is selected. In brackets, we label the hypotheses that we will test experimentally below.

**Proposition 1.**

(H1.1) *If states are independent, then the DM does not form a habit.*

(H1.2) *If states are persistent and the DM does not receive feedback, then she forms a habit with the cue  $a_1$ .*

(H1.3) *If states are persistent and the DM receives feedback, then she forms a habit with the cue  $\theta_1$ .*

We expect H1.1 and H1.3 to hold for a wide range of information-processing frictions. In contrast, H1.2 relies in a subtle way on the assumption of a posterior-separable cost. It may fail for alternative information-cost specifications, such as those in which the DM pays for a reduction of Gaussian noise. Recall from our definition that for  $a_1$  to be the habit cue, it must be that, conditional on  $(\theta_2, a_1)$ , the state  $\theta_1$  does not predict  $a_2$ . This is indeed the case under the posterior-separable cost function because each action  $a_1 = 0, 1$  corresponds to a unique information set; without feedback,  $a_1$  is a sufficient statistic for the DM's belief at the beginning of the second period. Under alternative specifications, such as the Gaussian one, each  $a_1 = 0, 1$  may correspond to multiple information sets. As a result,  $\theta_1$  may predict the DM's information set at the beginning of the second period, and hence indirectly predict  $a_2$ , controlling for  $(\theta_2, a_1)$ .

We turn now to the comparative-statics results. To proceed, we impose additional structure on the information-cost specification.

**Assumption A.** *The information-cost function  $H$  satisfies the following four properties:*

(A.1) *symmetry;  $H(q) = H(1 - q)$  for all  $q \in [0, 1]$ ,*

(A.2)  *$H$  is twice differentiable,*

(A.3)  *$H$  is steep at certainty;  $\lim_{q \rightarrow 0^+} H'(q) = \infty$ ,*

(A.4)  *$H''(q) \leq H''(q')$  for any  $q, q'$  such that  $|q - 1/2| > |q' - 1/2|$ .*

Observe that all four properties in Assumption A are satisfied by both Shannon entropy costs and by the log-likelihood cost function from Morris and Strack (2017).

When states are correlated and there is no feedback, information acquired in the first period has positive continuation value beyond its use in the first period choice. Thus, forward-looking subjects should acquire more information in the first period relative to the second one. The next result formalizes this intuition under Assumption A.

**Proposition 2** (H2). *Suppose that the cost function satisfies Assumption A. If the states are persistent and the DM does not receive feedback, then the DM chooses the correct action with higher probability in period 1 than in period 2,*

$$p(a_1 = \theta_1) > p(a_2 = \theta_2).$$

Finally, our last result establishes natural comparative-statics predictions of the habit strength with respect to stakes and state persistence  $\gamma$ . The proof of one of the results – comparative statics with respect to stakes in the setting without feedback, part (iii) below, exploits the functional form of the Shannon-entropy cost. The other comparative statics results are derived for all cost functions satisfying Assumption A.<sup>5</sup>

**Proposition 3.** *Suppose the states are persistent and the cost function satisfies Assumption A. Then the habit strength*

(i) *increases with the state persistence under both feedback treatments,*

(ii) *decreases with stakes in the presence of feedback,*

(iii) *also decreases with stakes in the absence of feedback, if the cost function is given by Shannon entropy.*

To economize on the number of the experimental treatments, we formulate a testable hypothesis that is coarser than the statement in Proposition 3.

**Hypothesis** (H3). *For each treatment with persistent states, the formed habits are stronger when persistence is high and stakes are low than when persistence is low and stakes are high.*

<sup>5</sup> Shannon entropy for a binary random variable is given by  $H_{\text{Shannon}}(q) = -q \log q - (1 - q) \log(1 - q)$ .



**Table 1**  
Hypotheses on habit formation for the eight experimental treatments.

Weak treatments			Strong treatments		
<i>high stakes</i>	<i>no feedback</i>	<i>feedback</i>	<i>low stakes</i>	<i>no feedback</i>	<i>feedback</i>
<i>state independence</i>	<i>no habit</i>	<i>no habit</i>	<i>state independence</i>	<i>no habit</i>	<i>no habit</i>
<i>low persistence</i>	<i>weak habit</i>	<i>weak habit</i>	<i>high persistence</i>	<i>strong habit</i>	<i>strong habit</i>
	with cue $a_1$	with cue $\theta_1$		with cue $a_1$	with cue $\theta_1$

**Table 2**  
Experimental treatments.

Weak treatments			Strong treatments		
<i>high stakes: \$10</i>	<i>no feedback</i>	<i>feedback</i>	<i>low stakes: \$7</i>	<i>no feedback</i>	<i>feedback</i>
<i>persistence <math>\gamma = .5</math></i>	<i>INW</i>	<i>IFW</i>	<i>persistence <math>\gamma = .5</math></i>	<i>INS</i>	<i>IFS</i>
<i>persistence <math>\gamma = .75</math></i>	<i>CNW</i>	<i>CFW</i>	<i>persistence <math>\gamma = .9</math></i>	<i>CNS</i>	<i>CFS</i>

### 3. Experimental design and data

Broadly, the structure of our design is as follows. We vary the experimental treatments along three dimensions: (i) we consider independent or positively serially correlated states, (ii) we provide feedback or not in terms of revealing  $\theta_1$  before the second period task, and (iii) we vary the stakes and the state correlation. Table 1 summarizes our hypotheses on habit formation, cue selection, and habit strength in the resulting eight treatments.

Our experimental subjects are incentivized to identify a binary state  $\theta_t$  in each period  $t = 1, 2$  by counting objects presented on a computer screen. Estimation (e.g., counting) procedures may differ in the induced error distributions of actions and in the associated cognitive and time costs. A subject's choice over procedures thus involves tradeoffs akin to those formally studied in the previous section.<sup>6</sup>

In more detail, subjects were presented with images of a  $10 \times 10$  matrix of red and blue dots on a computer screen. In each matrix, either 51 red and 49 blue (state  $\theta = 1$ ) or 51 blue and 49 red dots ( $\theta = 0$ ) are displayed. The positions of the colored dots are random conditional on the state; see the screenshot in Appendix A.3. Subjects are incentivized to determine the majority color and do not face explicit informational cost; any perception errors stem from frictions in the cognitive process. When a subject is ready, she enters her choice by clicking one of two radio buttons marked “Red” and “Blue”.<sup>7</sup> To ensure a reasonable duration of the experiment, each image disappeared after 45 seconds.<sup>8</sup> The experiments were implemented using z-tree (Fischbacher, 2007). We refer to the above one-period decision problem as the *counting task*.

We recruited 76 subjects from the University of California, Santa Barbara over 4 sessions during May 2018. In each session, subjects faced 4 treatments. Each treatment consisted of 12 iterations and each iteration consisted of the two-period decision problem described above, with one counting task per period. Thus, each subject faced  $96 = 4 \times 12 \times 2$  counting tasks in total. At the conclusion of the session, the software randomly chose a single counting task for each subject, and the subject's payment was based only on the outcome of that task.

An “iteration” is thus our basic unit of observation. In each iteration, both state realizations were equally likely in the first period:  $p_1 = 1/2$ . The four treatments per session are defined by the combinations of (i) the state persistence, where *I* denotes *independent* and *C* denotes *correlated* states, and (ii) whether  $\theta_1$  was revealed in between the two periods, where *F* denotes the provision of information feedback and *N* denotes no provision. In addition, in two of the sessions we used parameters that correspond to the hypothesis of inducing strong habits; treatments in these two sessions are denoted by *S*, and the treatments in the other two sessions are labeled by *W* (for weak habits). We thus have 8 treatments from the set  $\{I, C\} \times \{N, F\} \times \{W, S\}$ ; see Table 2. We randomly generated the state sequence once for each of the 8 treatments and used it in both sessions in which the treatment occurred. Within a treatment, each subject faced the same sequence of images. Each subject has participated in exactly one session. The 4 sessions featured the following sequences of the treatments, (*IFW*, *CFW*, *INW*, *CNW*), (*INW*, *CNW*, *IFW*, *CFW*), (*IFS*, *CFS*, *INS*, *CNS*), and (*INS*, *CNS*, *IFS*, *CFS*), respectively.

Additionally, we ran a preliminary session prior to the 4 regular sessions. The results from this session are consistent with those from the regular sessions. We omit this session from the analysis due to a minor error in the experimental procedure; see Appendix A.2.

Each session lasted approximately 90 minutes. In all cases, subjects received a \$10 show-up fee. Average total earnings per subject were \$17.27 paid in cash at the conclusion of the experiment. The expected marginal payoff for each correct answer was  $\$ \frac{10}{96} \approx \$1$  in *W* treatments and it was  $\$ \frac{7}{96} \approx \$0.07$  in *S* treatments which is comparable to incentives in Caplin and Dean (2013) that varied from \$.01 to \$.15. See Appendix A.3 for our experimental instructions.

<sup>6</sup> The real-effort task enhances the external validity of the procedure. The particular counting task, adapted from Caplin and Dean (2015), facilitates comparability with the active experimental literature on information processing.

<sup>7</sup> Since we are interested in serial correlations that arise in the absence of real switching costs, we set the positions of the blue and red radio buttons to randomly vary across tasks. Thus, provision of the same answer in consecutive periods does not arise from a mental or physiological advantage.

<sup>8</sup> The subjects could submit their choices after the image had disappeared. The time constraint was binding at similar levels across treatments, in only 2–3% of problems.

**Table 3**

Data summary.

	Frequency of $a_1 = \theta_1$	Frequency of $a_2 = \theta_2$	Frequency of $a_2 = a_1$	Frequency of $a_1 = \theta_2$
<i>INW</i>	.84	.86	.51	.50
<i>IFW</i>	.85	.85	.60	.61
<i>CNW</i>	.87	.86	.78	.74
<i>CFW</i>	.89	.90	.78	.77
<i>INS</i>	.87	.85	.51	.50
<i>IFS</i>	.82	.82	.53	.55
<i>CNS</i>	.84	.85	.91	.84
<i>CFS</i>	.86	.87	.75	.73

**Table 4**Average marginal treatment effects, (their standard errors), and the  $p$ -values in the second lines. Bold values indicate significance at the 1% level.

	<i>IFW</i>	<i>INW</i>	<i>CFW</i>	<i>CNW</i>
$a_1$	-.021 (.036)	.034 (.041)	.017 (.032)	<b>.191 (.051)</b>
	.548	.406	.603	.000
$\theta_1$	.071 (.043)	-.026 (.049)	<b>.258 (.058)</b>	.002 (.036)
	.092	.596	.000	.948
$\theta_2$	<b>.681 (.032)</b>	<b>.692 (.054)</b>	<b>.611 (.046)</b>	<b>.629 (.067)</b>
	.000	.000	.000	.000
	<i>IFS</i>	<i>INS</i>	<i>CFS</i>	<i>CNS</i>
$a_1$	-.031 (.037)	.037 (.045)	-.033 (.026)	<b>.511 (.110)</b>
	.401	.416	.204	.000
$\theta_1$	.009 (.040)	-.034 (.044)	<b>.498 (.098)</b>	omitted
	.817	.430	.000	
$\theta_2$	<b>.632 (.045)</b>	<b>.700 (.036)</b>	<b>.425 (.121)</b>	<b>.367 (.098)</b>
	.000	.000	.000	.000

#### 4. Results

We present basic summary statistics in Table 3. The aggregate accuracy of choices is relatively high and homogeneous across treatments and periods. Accuracy is heterogeneous at the individual level; the number of correctly answered tasks per subject varied from 46 to 96 out of 96 tasks. Mild action persistence in the treatment *IFW*, in which the frequency of  $a_1 = a_2$  is 0.60, is caused by the realized frequency of  $\theta_1 = \theta_2$  being 0.67 and by the subjects' attentiveness to the state realizations.<sup>9</sup>

To check for trends in choice accuracy over the duration of a session we ran a logit regression in which we explain whether subject's choice  $a_t$  is correct by the number of counting task pairs she has already encountered and by treatment dummies. We run two such separate regressions for  $t = 1, 2$ . In both cases, the length of the previous exposure is insignificant. Thus, we see no evidence of experience building or fatigue; see Section 1 of the regression supplement for details.

We proceed to test for the presence of habits and to identify the associated cues. To examine how  $\theta_1$  and  $a_1$  predict  $a_2$ , we run separate logit regressions for all 8 treatments of the form:

$$a_{2,i}^n = \begin{cases} 1 & \text{if } \beta_0 + \beta_{\theta_2}\theta_2^n + \beta_{\theta_1}\theta_1^n + \beta_{a_1}a_{1,i}^n + \beta_{se}session + \beta_{sc}score_i^n + \beta_{sc\theta_2}score_i^n\theta_2^n + \varepsilon_i^n > 0, \\ 0 & \text{otherwise,} \end{cases} \quad (1)$$

with robust standard errors clustered at the subject level, where  $a_{t,i}^n$  is the action taken by subject  $i$  in iteration  $n = 1, \dots, 12$  and period  $t = 1, 2$ ;  $\theta_t^n$  is the realized state in iteration  $n$  and period  $t$ ; and *session* is a dummy variable indicating session (each of the 8 treatments occurs in exactly two sessions).<sup>10</sup> Finally, we include the interaction term  $score_i^n\theta_2^n$  (and the term  $score_i^n$ ), where  $score_i^n$  is a subject-specific proxy for counting ability. It is the total number of correct answers by subject  $i$  in all treatments (excluding the two choices from iteration  $n$  of the considered treatment to avoid endogeneity). The interaction term  $score_i^n\theta_2^n$  captures the idiosyncratic sensitivity of the subjects to the variation in  $\theta_2$ . Otherwise, failing to account for heterogeneity in counting ability may lead to spurious significance of  $\theta_1$  in the correlated treatments without feedback: for a given  $a_1$ ,  $\theta_1 = a_1$  predicts high counting ability (i.e., low information cost) which, in turn, predicts  $a_2 = \theta_2$ . Hence, under state persistence, it predicts  $a_2 = \theta_1$ .

Table 4 reports the estimated average marginal effects, their standard errors and  $p$ -values of the explanatory variables of interest. We draw the following conclusions from this analysis.

<sup>9</sup> The frequency .67 of  $\theta_1 = \theta_2$  corresponds to 8 cases out of 12, which occurs with an a priori probability  $\binom{12}{8} \cdot 5^8 \cdot 5^4 \approx .12$ .

<sup>10</sup> In the treatment *CNS*, the state realizations satisfied  $\theta_1^n = \theta_2^n$  for all  $n$ , and thus we dropped  $\theta_1$  from that treatment's regression.



We first obtain the elementary confirmation that subjects pay attention to the payoff states.

**Result (R0).** Subjects pay attention to  $\theta_2$ :  $\theta_2$  predicts  $a_2$  in all treatments.

The next findings confirm Hypotheses H1.1, H1.2, and H1.3.

**Result.**

- (R1.1) When the states are independent, the subjects do not form habits: neither  $a_1$  nor  $\theta_1$  predict  $a_2$  in treatments *IFW*, *INW*, *IFS*, and *INS*.
- (R1.2) When the states are persistent and feedback is not provided, the subjects form a habit with cue  $a_1$ :  $a_1$  predicts  $a_2$  and  $\theta_1$  does not predict  $a_2$  in treatments *CNW* and *CNS*.
- (R1.3) When the states are persistent and feedback is provided, the subjects form a habit with cue  $\theta_1$ :  $\theta_1$  predicts  $a_2$  and  $a_1$  does not predict  $a_2$  in treatments *CFW* and *CFS*.

Next, we compare choice accuracy in the first and the second periods under persistent states without feedback (treatments *CNW* and *CNS*). For  $t = 1, 2$ , let  $r_t \in \{c, w\}$  indicate correct and wrong response in period  $t$ , respectively. We test the hypothesis that the marginal probabilities of correct answers are equal across the two periods,  $\Pr(r_1 = c) = \Pr(r_2 = c)$ . Since  $r_t$  are binary and correlated random variables, we apply McNemar's test; see McNemar (1947). We cannot reject the hypothesis of equal precisions both for the *CNW* treatment ( $p$ -value .29) and for the *CNS* treatment ( $p$ -value .42). Accordingly, the data do not confirm Hypothesis H2. We interpret this finding as indirect evidence of myopia in information acquisition, whereby subjects do not fully account for the positive continuation value of information under state persistence.

**Result (R2).** Choice accuracy does not differ significantly across the first and second periods in the treatments with persistent states and no feedback.

To analyze the comparative statics of habit strength, we focus on the four treatments with persistent states in which habits are formed, and we compare the habit strength across the weak and strong treatments. Specifically, for the treatments without feedback, we pool the data from *CNW* and *CNS* and create a dummy variable  $\delta \in \{0, 1\}$  to indicate treatment  $S$ . We run the same logit specification as in (1) with the inclusion of the additional variables  $\delta$ ,  $\delta\theta_2^n$ ,  $\delta a_{1,i}^n$ ,  $\delta score_i^n$ , and  $\delta score_i^n \theta_2^n$ .<sup>11</sup> Since the empirical habit cue is  $a_1$ , we estimate the difference between the average marginal effect of  $a_1$  conditional on  $\delta = 1$  ( $S$ ) and its average marginal effect conditional on  $\delta = 0$  ( $W$ ),

$$\Delta_{CN} = E_X [\Pr(a_2 = 1 \mid a_1 = 1, X, \delta = 1) - \Pr(a_2 = 1 \mid a_1 = 0, X, \delta = 1) - (\Pr(a_2 = 1 \mid a_1 = 1, X, \delta = 0) - \Pr(a_2 = 1 \mid a_1 = 0, X, \delta = 0))],$$

where  $X$  stands for all explanatory variables other than  $a_1$  and  $\delta$ . We obtain a point estimate  $\hat{\Delta}_{CN} = .31$  with standard error .12, which is highly significant ( $p$ -value .009).

Analogously, for the treatments with feedback, we pool the data from treatments *CFW* and *CFS* and create a dummy variable  $\delta \in \{0, 1\}$  to indicate the strong treatment. We run the regression model (1) with the inclusion of  $\delta$ ,  $\delta\theta_2^n$ ,  $\delta\theta_1^n$ ,  $\delta a_{1,i}^n$ ,  $\delta score_i^n$ , and  $\delta score_i^n \theta_2^n$ . As the habit cue in these treatments is  $\theta_1$ , we estimate the difference between the average marginal effect of  $\theta_1$  conditional on  $\delta = 1$  ( $S$ ) and its average marginal effect conditional on  $\delta = 0$  ( $W$ ),

$$\Delta_{CF} = E_X [\Pr(a_2 = 1 \mid \theta_1 = 1, X, \delta = 1) - \Pr(a_2 = 1 \mid \theta_1 = 0, X, \delta = 1) - (\Pr(a_2 = 1 \mid \theta_1 = 1, X, \delta = 0) - \Pr(a_2 = 1 \mid \theta_1 = 0, X, \delta = 0))].$$

Here, we obtain the point estimate  $\hat{\Delta}_{CF} = .23$  with standard error .12, which is marginally significant ( $p$ -value .06).

**Result (R3).** We find strong (suggestive) statistical evidence that the habit formed in the correlated treatments without (with) feedback is stronger in the treatment with high persistence and low incentives than in the treatment with low persistence and high incentives.

## 5. Summary

Our experiment reveals a significant degree of sophistication in habit formation, cue selection, and in the degree of habit strength. This sophistication favors, in the environment studied here, concepts of habits based on explicit optimization under

<sup>11</sup> We have excluded the interaction term  $\delta\theta_1^n$ , since the state realizations satisfied  $\theta_1^n = \theta_2^n$  for all  $n$  in *CNS*.

information frictions. A promising implication of these findings is that models of habits that are based on optimization of the relevant tradeoffs may provide us with useful comparative-statics predictions. Yet, despite the documented sophistication, our data also indirectly document myopia in information acquisition – a feature inconsistent with rational, forward-looking information-acquisition models.

## Appendix A

### A.1. Proofs

**Proof of Lemma 1.** We solve the problem backwards. Let  $p_2$  be the probability that the DM assigns to  $\theta_2 = 1$  at the beginning of the period 2. Let  $v(q) = s \max\{q, 1 - q\}$  be the DM's expected optimized second-period payoff at a given value of the posterior  $q = \Pr(\theta_2 = 1 \mid x_1, y, x_2)$ . The DM chooses a random second-period posterior  $\hat{q}_2$  that maximizes the second-period payoff net of the second-period information cost:

$$\begin{aligned} \max_{\hat{q}_2} & E_{\hat{q}_2} [v(\hat{q}_2) - H(p_2) + H(\hat{q}_2)] \\ \text{s.t.:} & E_{\hat{q}_2} \hat{q}_2 = p_2. \end{aligned}$$

We let  $w_2(p_2)$  be the value of the above problem. This second-period problem can be solved by the concavification of  $v(\cdot) + H(\cdot)$ ; see Caplin and Dean (2013). Since  $\theta_2$  has binary support, the support of the second-period posterior  $\hat{q}_2$  is at most binary. Additionally, due to our regularity condition, both  $a_2 = 0$  and  $a_2 = 1$  occur with positive probabilities, and thus the support of  $\hat{q}_2$  contains one value  $\underline{q}$  below and one value  $\bar{q}$  above  $1/2$ . The values  $\underline{q}$  and  $\bar{q}$  are independent of  $p_2$ .

In the setting without feedback,  $p_2$  attains the random value  $\hat{p}_2 = \gamma \hat{q}_1 + (1 - \gamma)(1 - \hat{q}_1)$  where  $\hat{q}_1 = \Pr(\theta_1 \mid x_1)$  is the random posterior at the end of the period 1. Let

$$v_1^n(q_1) = v(q_1) + w_2(\gamma q_1 + (1 - \gamma)(1 - q_1))$$

be the value of the DM whose first-period posterior belief  $\hat{q}_1$  attains value  $q_1$ ; it consists of the immediate expected payoff  $v(q_1)$  for the first-period action and of the continuation payoff  $w_2(\gamma q_1 + (1 - \gamma)(1 - q_1))$ . The DM chooses a random first-period posterior  $\hat{q}_1$  that solves

$$\begin{aligned} \max_{\hat{q}_1} & E_{\hat{q}_1} [v_1^n(\hat{q}_1) - H(p_1) + H(\hat{q}_1)] \\ \text{s.t.:} & E_{\hat{q}_1} \hat{q}_1 = p_1, \end{aligned}$$

where  $p_1$  is the prior probability that  $\theta_1 = 1$ . This problem can also be solved by concavification. Again, due to the binary support of  $\theta_1$  and the regularity condition,  $\hat{q}_1$  attains two values that we denote by  $\underline{q}^n < 1/2$  and  $\bar{q}^n > 1/2$ . Again, this support is independent of  $p_1$ .

In the setting with feedback,  $p_2$  attains the random value  $\hat{p}_2 = \gamma y + (1 - \gamma)(1 - y)$  and the DM solves

$$\begin{aligned} \max_{\hat{q}_1} & E_{\hat{q}_1} [v_1^f(\hat{q}_1) - H(p_1) + H(\hat{q}_1)] \\ \text{s.t.:} & E_{\hat{q}_1} \hat{q}_1 = p_1, \end{aligned}$$

where

$$v_1^f(q_1) = v(q_1) + E_y [w_2(\gamma y + (1 - \gamma)(1 - y))].$$

Since the continuation value  $w_2(\gamma y + (1 - \gamma)(1 - y))$  does not depend on the first-period posterior, the DM chooses the support of  $\hat{q}_1$  to be the same as that of  $\hat{q}_2$ ;  $\hat{q}_1$  attains values  $\underline{q}$  and  $\bar{q}$ , again, independently of  $p_1$ .

The joint distribution  $p(\theta_1, \theta_2, a_1, a_2)$  is uniquely determined by the binary supports of  $\hat{q}_1$  and  $\hat{q}_2$ .  $\square$

**Proof of Proposition 1.** *Statement 1.:* The support of the random second-period posterior is independent of the first-period posterior and of  $y$ . Since  $\theta_1$  and  $\theta_2$  are independent, the prior  $p_2$  at the beginning of period 2 is independent of  $\theta_1$  and  $a_1$ . Thus, the random second-period posterior (and hence  $a_2$ ) is a r.v. independent of  $\theta_1$  and  $a_1$ , conditionally on  $\theta_2$ , as needed.

*Statement 2.:*

$$\begin{aligned} p(a_2 = 1 \mid \theta_2, a_1 = 1, \theta_1) &= \Pr(\hat{q}_2(\hat{q}_1) = \bar{q} \mid \theta_2, \hat{q}_1 = \bar{q}^n), \\ p(a_2 = 1 \mid \theta_2, a_1 = 0, \theta_1) &= \Pr(\hat{q}_2(\hat{q}_1) = \bar{q} \mid \theta_2, \hat{q}_1 = \underline{q}^n). \end{aligned}$$

The right-hand sides do not depend on  $\theta_1$ , as needed. It suffices to prove that for each  $\theta_2 \in \{0, 1\}$ , the first expression exceeds the latter. We consider the case  $\theta_2 = 1$ ; the computation for  $\theta_2 = 0$  is analogous.

$$\begin{aligned}
p(a_2 = 1 \mid \theta_2 = 1, a_1 = 1) &= \Pr(\hat{q}_2(\hat{q}_1) = \bar{q} \mid \theta_2 = 1, \hat{q}_1 = \bar{q}^n) \\
&= \Pr(\theta_2 = 1 \mid \hat{q}_2(\hat{q}_1) = \bar{q}, \hat{q}_1 = \bar{q}^n) \frac{\Pr(\hat{q}_2(\hat{q}_1) = \bar{q} \mid \hat{q}_1 = \bar{q}^n)}{\Pr(\theta_2 = 1 \mid \hat{q}_1 = \bar{q}^n)} \\
&= \bar{q} \frac{\frac{\bar{q}^n \gamma + (1 - \bar{q}^n)(1 - \gamma) - \underline{q}}{\bar{q} - \underline{q}}}{\bar{q}^n \gamma + (1 - \bar{q}^n)(1 - \gamma)} \\
&= \frac{\bar{q}}{\bar{q} - \underline{q}} \frac{\bar{q}^n \gamma + (1 - \bar{q}^n)(1 - \gamma) - \underline{q}}{\bar{q}^n \gamma + (1 - \bar{q}^n)(1 - \gamma)} \\
&= \varphi(\bar{q}^n \gamma + (1 - \bar{q}^n)(1 - \gamma)),
\end{aligned}$$

where  $\varphi(p_2) = \frac{\bar{q}}{\bar{q} - \underline{q}} \frac{p_2 - \underline{q}}{p_2}$ . An analogous computation implies that  $p(a_2 = 1 \mid \theta_2 = 1, a_1 = 0) = \varphi(\underline{q}^n \gamma + (1 - \underline{q}^n)(1 - \gamma))$ . The claim follows from the monotonicity of  $\varphi$ .

**Statement 3.:** When the DM receives feedback, then her belief at the beginning of period 2 is  $\hat{p}_2 = \gamma \theta_1 + (1 - \gamma)(1 - \theta_1)$ . Since  $\hat{p}_2$  and the values of the second-period posteriors  $\bar{q}$  and  $\underline{q}$  do not depend on  $a_1$ ,  $p(a_2 \mid \theta_2, \theta_1, a_1)$  does not depend on  $a_1$ , as needed.

Let us consider  $\theta_2 = 1$  (the case of  $\theta_2 = 0$  is again analogous). The values of the second-period posteriors,  $\bar{q}$  and  $\underline{q}$ , are the same as in the setting without feedback. Thus again, as in the proof of Statement 2,

$$p(a_2 = 1 \mid \theta_2 = 1, \theta_1 = 1) = \varphi(\gamma) > \varphi(1 - \gamma) = p(a_2 = 1 \mid \theta_2 = 1, \theta_1 = 0). \quad \square$$

The next lemma is an auxiliary result that we use in the proof of Proposition 3. It characterizes the habit strength as a function of the posterior values. To economize on notation, we write from now on  $q_2 \in [1/2, 1) = p(\theta_2 = 1 \mid a_2 = 1) = \bar{q}$  for the higher of the two realizations of the second-period posterior, and we note that thanks to the symmetry of the setting,  $p(\theta_2 = 1 \mid a_2 = 0) = 1 - q_2$  both in the settings with and without feedback. Similarly, we write  $q_1 \in [1/2, 1)$  for the high realization of the first-period posterior  $p(\theta_1 = 1 \mid a_1 = 1)$  and note that  $p(\theta_1 = 1 \mid a_1 = 0) = 1 - q_1$  in the both settings. We recall that the value of  $q_1$  depends on the feedback specification. Finally, in the setting without feedback, we let  $p_2$  stand for the belief at the beginning of period 2 of the DM who chose  $a_1 = 1$  in period 1. It is  $p_2 = p(\theta_2 = 1 \mid a_1 = 1) = \gamma q_1 + (1 - \gamma)(1 - q_1)$ . We recall that the belief at the beginning of period 2 is  $\gamma \theta_1 + (1 - \gamma)(1 - \theta_1)$  in the setting with feedback.

## Lemma 2.

1. In the setting without feedback, the habit strength is

$$\phi_{a_1}(\theta_2) = \frac{p_2 + q_2 - 1}{q_2 - p_2} \frac{1 - p_2}{p_2}. \quad (2)$$

2. In the setting with feedback, the habit strength is

$$\phi_{\theta_1}(\theta_2) = \frac{\gamma + q_2 - 1}{q_2 - \gamma} \frac{1 - \gamma}{\gamma}. \quad (3)$$

(Observe that habit strength is independent of  $\theta_2$  in both cases.)

**Proof of Lemma 2.** *Statement 1.:* By its definition, habit strength when the cue is the first-period action is,

$$\begin{aligned}
\phi_{a_1}(\theta) &= \frac{p(a_2 = \theta \mid \theta_2 = \theta, a_1 = \theta)}{p(a_2 = \theta \mid \theta_2 = \theta, a_1 = 1 - \theta)} \\
&= \frac{p(\theta_2 = \theta \mid a_2 = \theta, a_1 = \theta)p(a_2 = \theta \mid a_1 = \theta)/p(\theta_2 = \theta \mid a_1 = \theta)}{p(\theta_2 = \theta \mid a_2 = \theta, a_1 = 1 - \theta)p(a_2 = \theta \mid a_1 = 1 - \theta)/p(\theta_2 = \theta \mid a_1 = 1 - \theta)}.
\end{aligned}$$

Since the posterior  $p(\theta_2 = \theta \mid a_2 = \theta, a_1)$  is independent of  $a_1$ ,

$$\begin{aligned}
\phi_{a_1}(\theta) &= \frac{p(a_2 = \theta \mid a_1 = \theta)/p(\theta_2 = \theta \mid a_1 = \theta)}{p(a_2 = \theta \mid a_1 = 1 - \theta)/p(\theta_2 = \theta \mid a_1 = 1 - \theta)} \\
&= \frac{(p_2 + q_2 - 1)/p_2}{(q_2 - p_2)/(1 - p_2)},
\end{aligned}$$

where we have used the martingale condition imposed on the second-period posteriors to derive  $p(a_2 = \theta | a_1 = \theta) = \frac{p_2 + q_2 - 1}{2q_2 - 1}$  and  $p(a_2 = \theta | a_1 = 1 - \theta) = \frac{q_2 - p_2}{2q_2 - 1}$ , and we have noted that  $p(\theta_2 = \theta | a_1 = \theta) = p_2$  and  $p(\theta_2 = \theta | a_1 = 1 - \theta) = 1 - p_2$ .

**Statement 2.:** When the cue is the first-period state then the habit strength is defined as

$$\begin{aligned}\phi_{\theta_1}(\theta) &= \frac{p(a_2 = \theta | \theta_2 = \theta, \theta_1 = \theta)}{p(a_2 = \theta | \theta_2 = \theta, \theta_1 = 1 - \theta)} \\ &= \frac{p(\theta_2 = \theta | a_2 = \theta, \theta_1 = \theta)p(a_2 = \theta | \theta_1 = \theta)/p(\theta_2 = \theta | \theta_1 = \theta)}{p(\theta_2 = \theta | a_2 = \theta, \theta_1 = 1 - \theta)p(a_2 = \theta | \theta_1 = 1 - \theta)/p(\theta_2 = \theta | \theta_1 = 1 - \theta)}.\end{aligned}$$

Since the posterior  $p(\theta_2 = \theta | a_2 = \theta, \theta_1)$  is independent of  $\theta_1$ ,

$$\begin{aligned}\phi_{\theta_1}(\theta) &= \frac{p(a_2 = \theta | \theta_1 = \theta)/p(\theta_2 = \theta | \theta_1 = \theta)}{p(a_2 = \theta | \theta_1 = 1 - \theta)/p(\theta_2 = \theta | \theta_1 = 1 - \theta)} \\ &= \frac{(\gamma + q_2 - 1)/\gamma}{(q_2 - \gamma)/(1 - \gamma)},\end{aligned}$$

where we have used the martingale condition imposed on the second-period posteriors to derive that  $p(a_2 = \theta | \theta_1 = \theta) = \frac{\gamma + q_2 - 1}{2q_2 - 1}$  and  $p(a_2 = \theta | \theta_1 = 1 - \theta) = \frac{q_2 - \gamma}{2q_2 - 1}$ .  $\square$

**Proof of Propositions 2 and 3.** *Setting without feedback:* Since the cost function is symmetric, the DM solves

$$\max_{q_1, q_2} \{s(q_1 + q_2) - H(p_1) + H(q_1) - H(\gamma q_1 + (1 - \gamma)(1 - q_1)) + H(q_2)\}.$$

The second-period posterior  $q_2 \geq 1/2$  solves the first-order condition

$$s = -H'(q_2). \quad (4)$$

Because  $-H'(q_2)$  increases on  $[1/2, 1)$  and attains values in  $[0, \infty)$ , (4) has a unique solution  $q_2 \in (1/2, 1)$  that increases with the stake  $s$ .

Similarly, letting

$$\tilde{H}(q) = H(q) - H(\gamma q + (1 - \gamma)(1 - q)),$$

$q_1 \geq 1/2$  solves

$$s = -\tilde{H}'(q_1). \quad (5)$$

By part A.4 of Assumption A,

$$\tilde{H}''(q) = H''(q) - (2\gamma - 1)^2 H''(\gamma q + (1 - \gamma)(1 - q)) < 0.$$

Thus,  $-\tilde{H}'(q_1)$  increases and attains values in  $[0, \infty)$  for  $q \in [1/2, 1)$ . Thus also (5) has a unique solution  $q_1 \in (1/2, 1)$  that increases with  $s$ . Additionally,  $q_2 < q_1$  because  $-H'(q) > -\tilde{H}'(q)$  for all  $q \in [1/2, 1)$ ; this proves Proposition 2.

To prove Proposition 3, we first analyze comparative statics with respect to  $\gamma$ . Posterior  $q_2$  is independent of  $\gamma$ . Posterior  $q_1$  increases with  $\gamma$  since  $-\tilde{H}'(q)$  decreases with  $\gamma$  for all  $q \in [1/2, 1)$ . Hence  $p_2 = \gamma q_1 + (1 - \gamma)(1 - q_1)$  increases with  $\gamma$  too. We notice from (2) that  $\frac{\partial \phi_{a_1}}{\partial p_2} > 0$ . Thus,  $\phi_{a_1}$  increases in  $\gamma$ , as needed.

We now examine comparative statics with respect to  $s$  under the assumption that  $H(\cdot)$  is Shannon entropy. We combine (4) and (5) to get

$$H'(q_2) = H'(q_1) - (2\gamma - 1)H'(\gamma q_1 + (1 - \gamma)(1 - q_1)),$$

and we express  $q_2$  as an increasing function of  $q_1$ . Using that  $H'(q) = \log \frac{1-q}{q}$ , we get

$$q_2(q_1) = \frac{1}{1+x},$$

with  $x = \frac{1-q_1}{q_1} \left( \frac{p_2}{1-p_2} \right)^{2\gamma-1} > 0$ , where we remind that  $p_2 = \gamma q_1 + (1 - \gamma)(1 - q_1)$  is a function of  $q_1$ . We prove that  $\frac{d^2 q_2}{dq_1^2}$  is positive.

$$\begin{aligned}
\frac{dq_2}{dq_1} &= \frac{-1}{(1+x)^2} \frac{dx}{dq_1} \\
&= \frac{-1}{(1+x)^2} \left( \frac{-1}{q_1^2} \left( \frac{p_2}{1-p_2} \right)^{2\gamma-1} + \frac{1-q_1}{q_1} \left( \frac{p_2}{1-p_2} \right)^{2\gamma-2} \frac{(2\gamma-1)^2}{(1-p_2)^2} \right) \\
&= \frac{-1}{(1+x)^2} \frac{1-q_1}{q_1} \left( \frac{p_2}{1-p_2} \right)^{2\gamma-1} \left( \frac{-1}{q_1(1-q_1)} + \frac{(2\gamma-1)^2}{p_2(1-p_2)} \right) \\
&= \frac{x}{(1+x)^2} \left( \frac{1}{q_1(1-q_1)} - \frac{(2\gamma-1)^2}{p_2(1-p_2)} \right). \\
\frac{d^2q_2}{dq_1^2} &= \frac{(1-x)}{(1+x)^3} \frac{dx}{dq_1} \left( \frac{1}{q_1(1-q_1)} - \frac{(2\gamma-1)^2}{p_2(1-p_2)} \right) + \frac{x}{(1+x)^2} \left( \frac{2q_1-1}{q_1^2(1-q_1)^2} - (2\gamma-1)^3 \frac{2p_2-1}{p_2^2(1-p_2)^2} \right) \\
&= -\frac{(1-x)x}{(1+x)^3} \left( \frac{1}{q_1(1-q_1)} - \frac{(2\gamma-1)^2}{p_2(1-p_2)} \right)^2 + \frac{x}{(1+x)^2} \left( \frac{2q_1-1}{q_1^2(1-q_1)^2} - (2\gamma-1)^3 \frac{2p_2-1}{p_2^2(1-p_2)^2} \right) \\
&= -\frac{(1-x)x}{(1+x)^3} \left( \frac{1}{q_1(1-q_1)} - \frac{(2\gamma-1)^2}{p_2(1-p_2)} \right)^2 + \frac{x}{(1+x)^2} \left( \frac{2q_1-1}{q_1^2(1-q_1)^2} - (2\gamma-1)^4 \frac{2q_1-1}{p_2^2(1-p_2)^2} \right) \\
&> \frac{x(2q_1-1)}{(1+x)^2} \left( -\left( \frac{1}{q_1(1-q_1)} - \frac{(2\gamma-1)^2}{p_2(1-p_2)} \right)^2 + \left( \frac{1}{q_1^2(1-q_1)^2} - \frac{(2\gamma-1)^4}{p_2^2(1-p_2)^2} \right) \right) \\
&= \frac{x(2q_1-1)}{(1+x)^2} \left( \frac{1}{q_1(1-q_1)} - \frac{(2\gamma-1)^2}{p_2(1-p_2)} \right) \frac{2(2\gamma-1)^2}{p_2(1-p_2)} \\
&> 0,
\end{aligned}$$

where we have used  $(2\gamma-1)(2q_1-1) = (2p_2-1)$  in the third step,  $\frac{1-x}{1+x} = 2q_2-1 < (2q_1-1)$  in the fourth step, and  $q_1 > p_2$  in the last step.

We notice from (2) that  $\phi_{a_1}$  decreases with  $s$  if  $\frac{p_2+q_2-1}{q_2-p_2}$  decreases with  $s$  (since  $\frac{1-p_2}{p_2}$  decreases with  $q_1$  and hence with  $s$ ). Thus,  $\phi_{a_1}$  decreases with  $s$  if

$$\begin{aligned}
0 &> \frac{d}{ds} \frac{p_2+q_2-1}{q_2-p_2} \\
&= \frac{(2q_2-1) \frac{dp_2}{ds} - (2p_2-1) \frac{dq_2}{ds}}{(q_2-p_2)^2} \\
&= \left( (2q_2-1) \frac{dp_2}{dq_1} - (2p_2-1) \frac{dq_2}{dq_1} \right) \frac{\frac{dq_1}{ds}}{(q_2-p_2)^2} \\
&= \left( (2q_2-1)(2\gamma-1) - (2p_2-1) \frac{dq_2}{dq_1} \right) \frac{\frac{dq_1}{ds}}{(q_2-p_2)^2} \\
&= \left( 2q_2-1 - (2q_1-1) \frac{dq_2}{dq_1} \right) \frac{(2\gamma-1) \frac{dq_1}{ds}}{(q_2-p_2)^2},
\end{aligned}$$

where we have used  $\frac{dp_2}{dq_1} = (2\gamma-1)$  for the third equality, and  $\frac{2p_2-1}{2\gamma-1} = 2q_1-1$  to establish the fourth equality. Therefore, it suffices to prove that

$$2q_2-1 < (2q_1-1) \frac{dq_2}{dq_1}.$$

We observe that  $q_2 = 1/2$  when  $q_1 = 1/2$ . Thus, by the Mean value theorem, there exists  $1/2 < \tilde{q}_1 < q_1$  such that,

$$2q_2-1 = (2q_1-1) \left. \frac{dq_2}{dq_1} \right|_{\tilde{q}_1} < (2q_1-1) \left. \frac{dq_2}{dq_1} \right|_{q_1},$$

where the inequality follows from the fact that  $\frac{dq_2}{dq_1}$  increases with  $q_1$ .

*Setting with feedback:* Again,  $q_2$  solves (4) and thus  $q_2$  increases with  $s$  and it is independent of  $\gamma$ . It follows from (3) that  $\phi_{q_1}$  increases with  $\gamma$ . Finally,  $\phi_{\theta_1}$  decreases with  $q_2$ , and hence with  $s$ .  $\square$

**Table 5**

Preliminary session: Data summary.

	Frequency of $a_1 = \theta_1$	Frequency of $a_2 = \theta_2$	Frequency of $a_2 = a_1$	Frequency of $a_1 = \theta_2$
<i>IF</i>	.73	.66	.54	.55
<i>IN</i>	.79	.79	.52	.49
<i>CF</i>	.82	.81	.73	.70
<i>CN</i>	.79	.74	.79	.70

**Table 6**Preliminary session: Average marginal treatment effects, (their standard errors), and the  $p$ -values in the second lines. Bold values indicate significance at the 1% level.

	<i>IF</i>	<i>IN</i>	<i>CF</i>	<i>CN</i>
$a_1$	-.029 (.091)	.037 (.056)	.037 (.055)	<b>.449 (.083)</b>
	.748	.501	.500	.000
$\theta_1$	.129 (.101)	-.023 (.046)	<b>.408 (.203)</b>	-.095 (.065)
	.203	.617	.000	.144
$\theta_2$	<b>.267 (.065)</b>	<b>.552 (.072)</b>	<b>.317 (.082)</b>	<b>.436 (.099)</b>
	.000	.000	.000	.000

### A.2. Preliminary Session

We ran a preliminary session prior to the regular sessions. Sixteen participating subjects obtained a \$15 show-up fee and an additional \$5 for a correct answer to the counting task (randomly selected at the end of the experiment). The parameters were:  $\gamma = .5$  in treatments with independent states (*I*) and  $\gamma = .75$  in treatments with correlated states (*C*). As in the regular sessions,  $\theta_1$  was revealed in between periods in the treatments *F* with feedback and it was not revealed in treatments *N* without feedback. The treatment order was *IF*, *CF*, *IN*, *CN*.

The basic data description in Table 5 and the estimated average marginal treatment effects in Table 6 are consistent with the results from the regular sessions. However, in this session, the subjects were free to leave immediately once they finished all their counting tasks in the last treatment (*CN*), which affected their information processing costs in an uncontrolled manner, and thus we omit the pilot data from the main analysis.

### A.3. Experimental instructions

#### Instructions

Welcome to the experiment! Please take a record sheet at the front if you don't have one already. Please do not use the computers during the instructions. When it is time to use the computer, please follow the instructions precisely. (Repeat if necessary.)

Please raise your hand if you need a pencil. Please put away and silence all your personal belongings, especially your phone. We need your full attention during the experiment.

Raise your hand at any point if you cannot see or hear well.

The experiment you will be participating in today is an experiment in decision making. At the end of the experiment, you will be paid for your participation in cash. The amount you earn depends on your decisions and on chance. You will be using the computer for the experiment, and all decisions will be made through the computer. DO NOT socialize or talk during the experiment.

All instructions and descriptions that you will be given in the experiment are accurate and true. In accordance with the policy of this lab, at no point will we attempt to deceive you in any way.

If you have any questions, raise your hand and your question will be answered out loud so everyone can hear.

After you have completed all the tasks, please wait while everyone else finishes his or her tasks. Once everyone has completed the experiment, I will ask you to fill in the questionnaire. After the questionnaire you will collect your earnings and leave.

////////////////////////////////////

I will now describe the main features of the experiment and show you how to use the software. Again, if you have any questions during this period, please raise your hand.

You will be presented with a series of choices to make. There will be four SETS of choices in today's experiment. Each set contains twelve ITERATIONS, and each iteration has two PERIODS. In each period, you will be shown a picture of 100 dots. Each dot will be either RED or BLUE. We have displayed an example of such a screen on your computer monitor (show an example screen Fig. 1).

This is an example of the screens you will see during the experiment. In every period, the picture will contain either 51 red dots and 49 blue dots, or instead, 51 blue dots and 49 red dots. We will call these two cases MAJORITY RED and



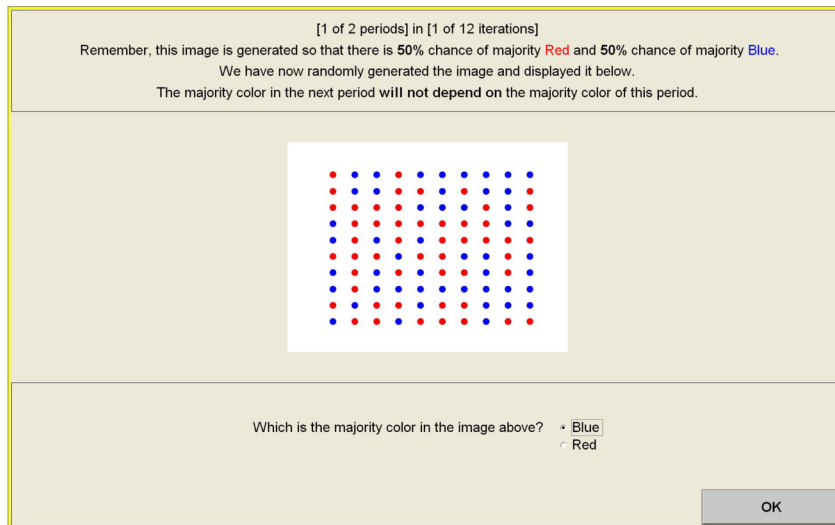


Fig. 1. A scaled-down screenshot of the counting task.

MAJORITY BLUE, respectively. In each case, the dots are randomly allocated to the positions in the matrix. In each period the computer will choose randomly between MAJORITY RED and MAJORITY BLUE. You will be told in advance how likely each case is to happen.

In each period, you will be asked to determine if the image is MAJORITY RED or MAJORITY BLUE. While you may take as much time as you need to make your choice, the image will disappear after 45 seconds.

I am now going to describe the details of the experiment.

The experiment is divided into four SETS. In each set, you will be presented with twelve iterations, and each iteration consists of two periods, each with its own image. The rules for the 12 iterations within each set are identical, but the rules are different in different sets.

In PERIOD 1 of each iteration, the image is always generated so that there is an equal chance of MAJORITY RED and MAJORITY BLUE, meaning that there is a 50% chance of MAJORITY RED and a 50% chance of MAJORITY BLUE.

In period 2 of each iteration, the image will be generated in a way that differs across sets. In some sets, the majority color for period 2 is chosen in a way that is completely separate from the period 1 image, and is randomly generated so that there is an equal chance of MAJORITY RED and MAJORITY BLUE, just like the period 1 image. But in other sets, the period 2 image depends on the majority color of the period 1 image. In these sets, the computer generates the period 2 image so that there is a 75% chance that the majority color matches the period 1 majority color, and a 25% chance that the majority color is different from the period 1 majority color.

It is important to remember that while the periods within each iteration may be related to each other, the periods across iterations are never related.

After making your choices, you will always be told what the majority color was, but the timing of this differs from set to set. In some sets, the majority colors will be revealed after every period. In other sets, the majority colors for an iteration will not be revealed until you complete both periods. Before each set, you will be told about the timing of the feedback you will receive.

The amount of money you will receive at the end of the experiment depends on your choices. After we have completed all four sets, you will have made 96 choices (4 sets times 12 iterations times 2 periods). The computer software will randomly select one of these 96 periods. Your payment will be determined by your choice in that single period. If your choices in the randomly chosen period matches the majority color, you will earn an additional \$5 dollars on top of the \$15 show-up fee. Otherwise, you will receive no additional payment, but you will still receive the show-up fee.

After you complete the last set, please wait until we start the questionnaire part. After you finish the questionnaire, please fill your record sheet on the desk. I will pay one by one to keep everyone's privacy.

To summarize, remember that we have four sets in the experiment today. Each set consists of 12 iterations, and each iteration consists of two periods. The sets will vary in how likely it is that the majority colors are the same for both periods within an iteration, and in the timing that the majority colors are revealed. Please raise your hand if you have any questions.

(1) FI/FC/NI/NC

Feedback/IID:

In the next set of twelve iterations, the majority color for period 2 is randomly generated so that there is an equal chance of MAJORITY RED and MAJORITY BLUE, and it does not depend on the majority color in the first period.

The majority colors will be revealed after every period, so that you will be told the majority color from period 1 before you see the image for period 2. Please raise your hand if you have any question.

*Feedback/Corr.:*

In the next set of twelve iterations, the majority color for period 2 is randomly generated so that there is a 75% chance that the majority color matches the majority color from period 1, and a 25% chance that the majority color is different from period 1.

The majority colors will be revealed after every period, so that you will be told the majority color from period 1 before you see the image for period 2. Please raise your hand if you have any question.

*No Feedback/IID:*

In the next set of twelve iterations, the majority color for period 2 is randomly generated so that there is an equal chance of MAJORITY RED and MAJORITY BLUE, and it does not depend on the majority color in the first period.

The majority colors for both periods of an iteration will be revealed only at the end of each iteration, so that you will see the period 2 image before being told the majority color from period 1. Please raise your hand if you have any question.

*No Feedback/Corr.:*

In the next set of twelve iterations, the majority color for period 2 is randomly generated so that there is a 75% chance that the majority color matches the period 1 majority color, and a 25% chance that the majority color is different from the period 1 majority color.

The majority colors for both periods of an iteration will be revealed only at the end of each iteration, so that you will see the period 2 image before being told the majority color from period 1. Please raise your hand if you have any question.

*(2) NI/NC/FI/FC*

*No Feedback/IID:*

In the next set of twelve iterations, the majority color for period 2 is randomly generated so that there is an equal chance of MAJORITY RED and MAJORITY BLUE, and it does not depend on the majority color in the first period.

The majority colors for both periods of an iteration will be revealed only at the end of each iteration, so that you will see the period 2 image before being told the majority color from period 1. Please raise your hand if you have any question.

*No Feedback/Corr.:*

In the next set of twelve iterations, the majority color for period 2 is randomly generated so that there is a 75% chance that the majority color matches the period 1 majority color, and a 25% chance that the majority color is different from the period 1 majority color.

The majority colors for both periods of an iteration will be revealed only at the end of each iteration, so that you will see the period 2 image before being told the majority color from period 1. Please raise your hand if you have any question.

*Feedback/IID:*

In the next set of twelve iterations, the majority color for period 2 is randomly generated so that there is an equal chance of MAJORITY RED and MAJORITY BLUE, and it does not depend on the majority color in the first period.

The majority colors will be revealed after every period, so that you will be told the majority color from period 1 before you see the image for period 2. Please raise your hand if you have any question.

*Feedback/Corr.:*

In the next set of twelve iterations, the majority color for period 2 is randomly generated so that there is a 75% chance that the majority color matches the majority color from period 1, and a 25% chance that the majority color is different from period 1.

The majority colors will be revealed after every period, so that you will be told the majority color from period 1 before you see the image for period 2. Please raise your hand if you have any question.

## Appendix B. Supplementary material

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.geb.2020.04.013>.

## References

- Abel, A., 1990. Asset prices under habit formation and catching up with the Joneses. *Am. Econ. Rev.* 80 (2), 38–42.
- Andrews, B.R., 1903. Habit. *Am. J. Psychol.* 14 (2), 121–149.
- Angeletos, G.-M., Huo, Z., 2018. *Collective Myopia and Habit*. 236. Society for Economic Dynamics.
- Camerer, C., Landry, P., Webb, R., forthcoming. The neuroeconomics of habit. In: A. Kirman, M. Tedeschi (Eds.), *The State of the Mind*, Oxford University Press.

- Caplin, A., Dean, M., 2013. Behavioral implications of rational inattention with Shannon entropy. Technical report, National Bureau of Economic Research Working Paper 19318.
- Caplin, A., Dean, M., 2015. Revealed preference, rational inattention, and costly information acquisition. *Am. Econ. Rev.* 105 (7), 2183–2203.
- Caplin, A., Dean, M., Leahy, J., 2017. Rationally inattentive behavior: characterizing and generalizing Shannon entropy. National Bureau of Economic Research. Working Paper Series No. 23652.
- Dezfouli, A., Balleine, B.W., 2012. Habits, action sequences and reinforcement learning. *Eur. J. Neurosci.* 35 (7), 1036–1051.
- Fischbacher, U., 2007. z-tree: Zurich toolbox for ready-made economic experiments. *Exp. Econ.* 10 (2), 171–178.
- Khaw, M.W., Stevens, L., Woodford, M., 2017. Discrete adjustment to a changing environment: experimental evidence. *J. Monet. Econ.* 91, 88–103.
- Khaw, M.W., Zorrilla, O., 2018. Deeper Habits.
- Laibson, D., 2001. A cue-theory of consumption. *Q. J. Econ.* 116 (1), 81–119.
- Lally, P., Van Jaarsveld, C.H., Potts, H.W., Wardle, J., 2010. How are habits formed: modelling habit formation in the real world. *Eur. J. Soc. Psychol.* 40 (6), 998–1009.
- Mackowiak, B., Wiederholt, M., 2009. Optimal sticky prices under rational inattention. *Am. Econ. Rev.* 99 (3), 769–803.
- Matějka, F., McKay, A., 2015. Rational inattention to discrete choices: a new foundation for the multinomial logit model. *Am. Econ. Rev.* 105 (1), 272–298.
- McNemar, Q., 1947. Note on the sampling error of the difference between correlated proportions or percentages. *Psychometrika* 12 (2), 153–157.
- Morris, S., Strack, P., 2017. The Wald problem and the equivalence of sequential sampling and static information costs. SSRN Electron. J.
- Pollak, R.A., 1970. Habit formation and dynamic demand functions. *J. Polit. Econ.* 78 (4, Part 1), 745–763.
- Roth, A.E., Erev, I., 1995. Learning in extensive-form games: experimental data and simple dynamic models in the intermediate term. *Games Econ. Behav.* 8 (1), 164–212.
- Schmitt-Grohé, S., Uribe, M., 2007. Habit Persistence, second edition. The New Palgrave Dictionary of Economics. Palgrave Macmillan, NY.
- Sims, C.A., 2003. Implications of rational inattention. *J. Monet. Econ.* 50 (3), 665–690.
- Steiner, J., Stewart, C., Matějka, F., 2017. Rational inattention dynamics: inertia and delay in decision-making. *Econometrica* 85 (2), 521–553.
- Watkins, C.J., Dayan, P., 1992. Q-learning. *Mach. Learn.* 8 (3–4), 279–292.
- Wood, W., Neal, D.T., 2007. A new look at habits and the habit-goal interface. *Psychol. Rev.* 114 (4), 843.